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# A Novel Implementation of QuickHull Algorithm on the GPU

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## Abstract

We present a novel GPU-accelerated implementation of the QuickHull algorithm for calculating convex hulls of planar point sets. We also describe a practical solution to demonstrate how to efficiently implement a typical Divide-and-Conquer algorithm on the GPU. We highly utilize the parallel primitives provided by the library *Thrust* such as the parallel segmented scan for better efficiency and simplicity. To evaluate the performance of our implementation, we carry out four groups of experimental tests using two groups of point sets in two modes on the GPU K20c. Experimental results indicate that: our implementation can achieve the speedups of up to 10.98x over the state-of-art CPU-based convex hull implementation Qhull [16]. In addition, our implementation can find the convex hull of 20M points in about 0.2 seconds.

**Keywords:** GPU; Parallelization; Convex Hull; QuickHull; Divide-and-Conquer

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## 1 Introduction

The calculating of the convex hull of a set of planar points is to find the convex polygon that encloses all the points. Several classic algorithms have been developed since 1970, including the Graham scan [8], Gift wrapping [9], Incremental method [11], Divide-and-Conquer [15], Monotone chain [1], and QuickHull [2]. Several recent efforts have also been conducted to develop efficient convex hull algorithms [24, 12].

The finding of convex hulls of large sets of points is in general computationally expensive. An effective strategy for dealing with this problem is to calculate convex hulls in parallel. In recent years, to improve the computational efficiency of calculating convex hulls, several worthwhile contributions have been made to re-design and implement sequential convex hull algorithms in parallel by exploiting the power of massively computing on the GPU [18, 10, 19, 20, 21, 22, 23, 6, 7]. Most of these GPU-accelerated implementations are developed based upon the famous QuickHull algorithm [2].

For example, Srikanth, Kothapalli, Govindarajulu and Narayanan [18] first parallelized the QuickHull algorithm to accelerate the calculating of 2D convex hulls; and then Srungarapu, Reddy, Kothapalli

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and Narayanan [19] improved the above work and achieved better efficiency. Tzeng and Owens [22] presented a framework for accelerating the computing of convex hull in the Divide-and-Conquer fashion by taking advantage of QuickHull. Similarly, by also utilizing the QuickHull approach, Stein, Geva and El-Sana [20] presented a novel GPU-accelerated implementation of 3D convex hull algorithm.

In this paper, we present a novel GPU-accelerated implementation of the famous QuickHull algorithm for computing the convex hulls of planar point sets. We also describe a practical solution to demonstrate how to implement a typical Divide-and-Conquer algorithm on the GPU. Our implementation is quite similar to the one introduced by Tzeng and Owens [22]; but there are several significant differences between our implementation and that of Tzeng and Owens. Our implementation can achieve a speedup of up to 10.98x over a standard sequential CPU implementation, and can find the convex hull a set of 20M points in about 0.2 seconds.

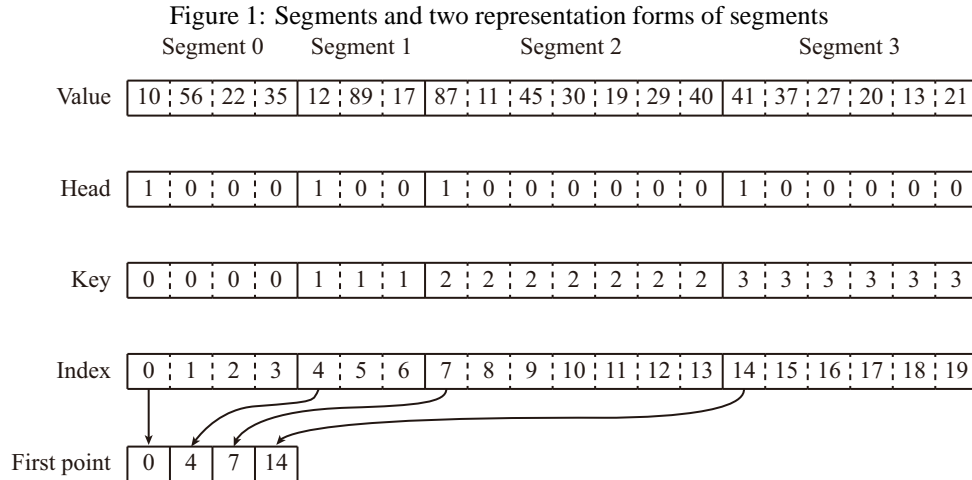
The rest of the paper is organized as follows. Section 2 introduces several background concepts behind our implementation. Section 3 describes the basic ideas behind our implementation. Section 4 further presents some implementation details. Then Section 5 gives several groups of experimental results, while Section 6 discusses the result. Finally, Section 7 concludes this work.

## 2 Segment and Segmented Scan

Segments are contiguous partitions of the data which are maintained by segment flags [4, 17]. There are typically two forms for representing segments: the first one is to use a set of head flags; and the other is to use a set of keys; see Figure 1. A head flag marks the beginning of a segment (called the segment *head*). A key indicates the index of the segment that each element / value in a given array belonging to.

Segmented scan generalizes the scan primitive by allowing scans on arbitrary segments (“partitions”) of the input vector [4]. To implement segmented scan in parallel, Sengupta, Harris, Zhang and Owens [17] introduced the segmented scan primitive to the GPU. And currently both the libraries CUDPP [5] and Thrust [3] both provide efficient GPU-accelerated segmented scan primitives.

Thrust is a C++ template library for CUDA based on the Standard Template Library (STL). Thrust allows users to implement high performance parallel applications with minimal programming effort through a high-level interface that is fully interoperable with CUDA C [14]. Thrust provides a rich collection of data structures and data parallel primitives such as scan, sort, and reduce, which can be composed together to implement complex algorithms with concise, readable source code.



### 3 Basic Ideas behind Our Implementation

The most important idea behind our implementation is to directly operate the data in the input arrays that are originally allocated to store the coordinates of input points, rather than in the additionally allocated arrays or splitting the input data into separate arrays.

The QuickHull algorithm is a Divide-and-Conquer method, which tends to divide the input data set into subsets and then handles these subsets recursively. On the GPU, an effective strategy is to divide the input data set into subsets, but do not store them in separated arrays with different sizes. Instead, all the data of the subsets are still stored in the input data array, but the data of each subset is stored into a *Segment* (i.e., a consecutive piece / partition of data) [4]. Operations carried out for each subset is exactly the operations for each segment [22]. We adopt this strategy to develop our implementation.

Figure 2: Procedure of the 2D CUDA QuickHull on the GPU (without preprocessing)

**Procedure:** 2D Quickhull on the GPU  
*Input:* a set of input points  $pt\_in$   
*Output:* convex hull  $ch\_out$

**First Split**

- 1: Use parallel reduction to find the leftmost point  $P_{minx}$  and the rightmost point  $P_{maxx}$
- 2: Determine the positions of the rest points against the line  $P_{minx}P_{maxx}$   
 Assign a flag value to indicate the position:  $flag = 1$  when below;  $flag = 0$  when above
- 3: Use parallel partition to split the points into two segments according to the flag values:  
 the lower subset  $S_{lower}$  and the upper subset  $S_{upper}$
- 4: Use parallel sorting to sort the  $S_{lower}$  in  $x$ -ascending and  $S_{upper}$  in  $x$ -descending

**Recursive Step**

**Repeat**

**for** each segment  $(P_{first}, P_{last})$  represented by two points  $P_{first}$  and  $P_{last}$  **do**

- 5: Find the farthest point  $P_{far}$  from the line  $P_{first}P_{last}$
- 6: Divide segment  $(P_{first}, P_{last})$  into two new segments  $(P_{first}, P_{far})$  and  $(P_{far}, P_{last})$
- 7: Update all segments (including head flags, keys, first points)
- 8: Detect interior points by determining the positions
- 9: Assign each point a state flag depending on its position to indicate the state:  
 1: current non-interior points; 0: determined interior points
- 10: Use parallel stable\_partition to gather all interior points according to the state flags,  
 then remove all interior points
- 11: Update only the first points of all segments

**Until** there are no interior points can be found

12: Output the remaining points in  $pt\_in$  as the extreme points of  $ch\_out$

The procedure of our implementation is presented in Figure 2. In our implementation, after splitting the input set of points into the lower and the upper subsets, we sort the two subsets separately according to the  $x$ -coordinates. After this sorting, either the lower or the upper subset of sorted points can be considered as a *Monotone Chain* [1]; in addition, both the above chains can be further considered as two halves of a general polygon. If we detect and remove those vertices of the general polygon that have the interior angles greater than 180 degrees, then we can obtain the desired convex hull. The above idea of first sorting and then removing non-extreme points / concave vertices was introduced in [1] and [13].

Therefore, the basic idea behind our implementation is to “Find-and-Remove”. In the step of first split, we divide the input points and then sort them to **virtually** form a general polygon. In the subsequent recursive step, we recursively first *find* those non-extreme points, and then *remove* them to guarantee that all the remaining points are completely extreme points of the expected convex hull.

## 4 Implementation Details

### 4.1 Data Storage and Data Layout

We allocate several arrays on the device side to store the coordinates of planar points, information about segments, and other required values such as distances; see Table 1.

Table 1: Allocated arrays for storing data on the device

Array	Usage
float <code>x[n]</code>	$x$ coordinates
float <code>y[n]</code>	$y$ coordinates
float <code>dist[n]</code>	Distances
int <code>head[n]</code>	Indicator of the first point of each segment (1: Head point; 0: Not a head point)
int <code>keys[n]</code>	Index of the segment that each point belongs to
int <code>first_pts[n]</code>	Index of the first point of each segment
int <code>flag[n]</code>	Indicate whether a point is an extreme point or an interior point (1: Potential extreme point; 0: Determined interior point)

### 4.2 The Preprocessing Procedure

Before performing the QuickHull algorithm on the GPU, we first carry out a preprocessing procedure to filter the input points. The objective of this preprocessing procedure is to reduce the number of points by discarding those points that are not needed for consideration in the subsequent stage of calculating the desired convex hull.

We use the parallel reduction to find the extreme points with min or max  $x$  or  $y$  coordinate. In more details, we adopt the `thrust::minmax_element(x.begin(), x.end())` to find the leftmost and the rightmost points, and similarly use the `thrust::minmax_element(y.begin(), y.end())` to obtain the topmost and the bottommost points. These four extreme points are then used to form a convex quadrilateral.

We also design a simple CUDA kernel to check each point to determine whether it locates inside the quadrilateral. In the kernel, each thread is responsible for determining the position of only one point  $P_i$ , i.e., whether or not a point falls into the formed convex quadrilateral. If does, the corresponding indicator value `flag[i]` will be set to 0, otherwise, the value `flag[i]` is still kept as 1.

### 4.3 The First Split

The first split of the QuickHull algorithm is to divide the set of input points into two subsets, i.e., the lower and the upper subsets, using the line segment  $L$  formed by the leftmost and the rightmost points. Those points that locate below the  $L$  are grouped into the lower subset, while the ones distributed above the  $L$  are contained in the upper subset.

We develop another quite simple kernel to perform the above split procedure. In this kernel, each thread takes the responsibility to determine the position of only one point with respect to the line segment  $L$ . In this step, we temporarily use the values `int flag[n]` to indicate the positions: if the point  $P_i$  locates below the  $L$ , in other words, if  $P_i$  belongs to the lower subset, then the corresponding indicator value `flag[i]` will be set to 1, otherwise 0.

After determining the positions of all points, it is needed to gather the points belonging to the same subset such as the lower one together according to the indicator values `int flag[n]`. We realized this procedure by simply using the function `thrust::partition()`. Those points with the indicator value 1, i.e., the lower points, will be placed into the first consecutive half of the input array (a segment of points), while the upper points will be grouped into another consecutive half (another segment of points). In subsequent steps, operations will be performed in the segments of points.

## 4.4 The Recursive Procedure

### 4.4.1 Finding the Farthest Point

The first step in the recursive procedure is to find the farthest points in each segment, which includes two remarkable issues. The first is to calculate the distance for all points in parallel; and the other is to find those points with the farthest distances for all segments in parallel.

**Calculating the Distance.** The calculation of the distance from a point to a line is quite straightforward. However, in our implementation, it is needed to calculate the distances from different points to different lines simultaneously in parallel. This calculation is not so easy to implement in practice. This is because that: (1) for each segment, it is needed to compute the distance from each of those points belonging to this segment to the line formed by the first points and the last point; (2) for any two segments, their first point and last points are different.

In our implementation, for each point  $P_i$ , we use the value `first_pt[i]` to record the index of the first point of that segment it belongs to. Since segments are stored consecutively, the first point of the  $(j+1)^{th}$  segment is exactly the last point of the  $j^{th}$  segment except for the last segment. Note that the last point of the last segment is the point  $P_0$ . Therefore, it is easy to obtain the index of the last point for each segment, and the distance from the point  $P_i$  to the line formed by the first point and the last point.

**Find the Farthest Point.** After calculating the distances for those points in different segments, it is needed to find the farthest point in each segment. The finding of the farthest points for all segments in parallel is not so easy. This is because there are more than two segments that are needed to find their farthest points. Their farthest points are private, segment-specific. In this case, it is unable to perform a global parallel reduction, but is able to employ a segmented parallel reduction to find the greatest distance for each segment of points.

The segmented parallel reduction is designed in Thrust to make a parallel reduction for more than one segment of points. It can be used to find the min or max values in several segments in parallel. We employ the parallel primitive `thrust::reduce_by_key()` in our implementation to find the farthest points / maximum distances for all segments in parallel.

### 4.4.2 The First Round of Updating Segments

After finding the farthest points, each segment is then typically divided into two smaller sub segments using the farthest point. This means that the old segments are replaced with new segments. To create new segments, the following information of segments is needed to be updated:

#### (1) Head flags

The head flags of the farthest points are needed to be modified from 0 to 1, which means each of the farthest points becomes the first point of a new segment and a determined extreme points of the desired convex hull. The head flags of other points are kept unchanged.

#### (2) Keys

The updating of keys can be very easily realized by performing a global inclusive scan for the head flags. For that in each segment only the head flag of the first point is 1, the sum of the head flags can be considered as the index of the segment (i.e., the keys). Noticeably, the sum of the head flags is one-based

rather than zero-based (i.e., starting from 1 rather 0). To make the indices become much easier to be used, we further modify the keys from one-based to zero-based by performing a parallel subtracting.

### (3) Indices of first points

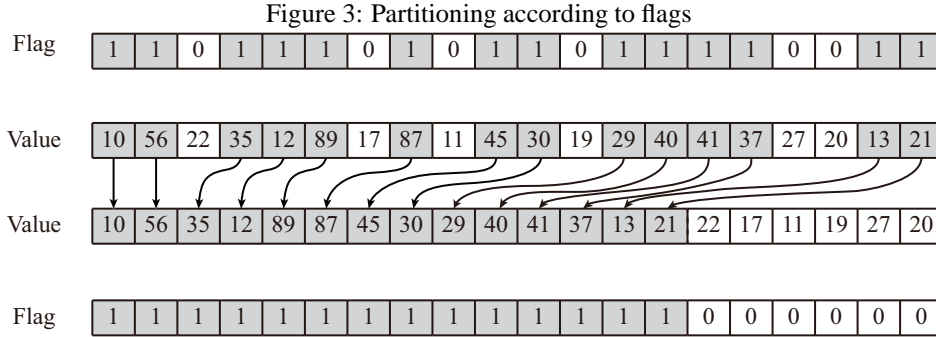
After updating the head flags and keys of each segment, the corresponding indices of the first points are no longer valid, and thus needed to be updated. Before updating the indices of the first points, we first assign a global index for each of the remaining points, then check each point whether it is the first point according to the head flags. If the head flag of a point  $P_i$  is 1, then this point must be a first point of a segment and its index is exactly  $i$ .

#### 4.4.3 Discarding Interior Points

The discarding of interior points is to first check whether or not a point locates inside the triangle formed by the first point of the segment (denoted as A), the last point of the segment (denoted as B), and the farthest point in this segment (denoted as C).

Let  $\triangle ACB$  denote the triangle, the determining of the points' positions with respect to the triangle  $\triangle ACB$  is to check whether those points in this segment locate on the right side of the directed line AC and the directed line CB. If does, then it is not an interior point, and its corresponding indicator value `flag[i]` is set to 1; otherwise, it is an interior point and the value `flag[i]` must modified to 0. Similarly, for each point in the segment (C,B), it is only needed to check whether it falls on the right side the directed line CB.

After determining all interior points in this recursion, we employ a parallel partitioning procedure to gather all interior points together according to the indicator values `int flag[n]`; see a simple illustration in Figure 3. Noticeably, to maintain the relative order of input points, we use the function `thrust::stable_partition()` rather than the function `thrust::partition()`. After the partitioning, we make an operation `resize()` to remove all the interior points found in this recursion.



#### 4.4.4 The Second Round of Updating Segments

This round of updating the segments is nearly the same to the first round of updating. The reason why this round of updating is needed to be performed is that: after removing some interior points, the points belonging to some segments are removed. In this case, the global indices of all the remaining point are not consecutive and thus need to be rearranged; see the first round of updating for more details about the above updating. Noticeably, the head flags and the keys for the remaining points are still correct, and do not need to be updated. Only the index of the first point of each segment needs to be updated.

## 5 Results

We perform our experimental tests using the NVIDIA Tesla K20c graphics card with 4GB memory and CUDA v5.5. The CPU experiments are performed on Windows 7 SP1 with an Intel E5-2650 (2.60GHz) and 96GB of RAM memory. Two groups of test data is employed in two modes to evaluate the performance of our implementation. The first group of test data includes 8 sets of points that randomly distributed in the unit square. The other group of test data is derived from publicly available 3D mesh models by projecting all vertices of each mesh model into the XY plane. These mesh models are directly obtained from the Stanford 3D Scanning Repository and the GIT Large Geometry Models Archive. In addition, we carry out the experimental tests in two modes: (a) Mode 1: in this mode, the preprocessing procedure is employed, (b) Mode 2: in this mode, the preprocessing procedure is not used.

We test the efficiency of our implementation using the points that are randomly distributed in the unit square and the points derived from 3D mesh models, and then compare the efficiency with that of the Qhull library; see Tables 2 and 3. The experimental results show that: our implementation can achieve the speedups of up to 10.98x and 8.30x in the Mode 1 and Mode 2, respectively. In addition, it costs about 0.2 seconds to compute the convex hull of 20M points in the best case.

Table 2: Comparison of running time (/ms) for points distributed in a square on K20c

Size	Qhull	Our implementation		Speedup	
		Mode 1	Mode 2	Mode 1	Mode 2
100K	16	37.2	61.7	0.43	0.26
200K	32	36.4	65.7	0.88	0.49
500K	62	41.7	69.2	1.49	0.90
1M	109	44.8	73.9	2.43	1.47
2M	234	55.9	86.2	4.19	2.71
5M	561	77.9	118.5	7.20	4.73
10M	1029	124.7	161.7	8.25	6.36
20M	2262	206.0	272.5	10.98	8.30

Table 3: Comparison of running time (/ms) for points derived from 3D models on K20c

3D Model	Size	Qhull	Our implementation		Speedup	
			Mode 1	Mode 2	Mode 1	Mode 2
Armadillo	172K	16	47.5	61.7	0.34	0.26
Angel	237K	47	50.5	62.6	0.93	0.75
Skeleton Hand	327K	32	49.5	61.8	0.65	0.52
Dragon	437K	62	55.9	67.4	1.11	0.92
Happy Buddha	543K	63	56.8	76.7	1.11	0.82
Turbine Blade	882K	125	64.3	72.3	1.94	1.73
Vellum Manuscript	2M	219	63.2	91.5	3.47	2.39
Asian Dragon	3M	359	78.4	129.8	4.58	2.77
Thai Statue	5M	515	84.4	142.6	6.10	3.61
Lucy	14M	1404	141.3	223.3	9.94	6.29

## 6 Discussion

### 6.1 Comparison

The basic ideas behind our implementation is similar to those behind the implementation of Tzeng and Owens [22]. The first of the same ideas is that: we perform the Divide-and-Conquer operations directly in the input arrays (i.e., the input sets of points), rather than on additionally allocated arrays. The second is that: the Divide-and-Conquer procedures of QuickHull algorithm are realized by creating, updating, or removing *Segments*. The third similar feature is that: both of the implementations are developed by strongly exploiting the data-parallel primitives, parallel (global) scan and parallel segmented scan.

However, we have our own ideas; and there are several significant differences. The first difference is that: after dividing the input set of points into the lower and the upper subsets, we further sort the above two subsets separately according to the  $x$ -coordinates, and maintain the relative order of those sorted points unchanged in the subsequent procedure of recursively removing interior points. In contrast, Tzeng and Owens [22] do not sort the subsets of points or keep the relative order of points.

The second difference is the creating and removing of segments: Tzeng and Owens create new segments using the farthest point by permuting the points located in the old segment, while we also create new segments using the farthest point but we do not permute points. When removing segments, we at least retain the first point (i.e., the head point) of each segment for that this point is definitely an extreme point of the desired convex hull, while in the implementation of Tzeng and Owens a segment is probably completely removed. This difference is due to the different schemes of updating segments.

Another difference is that: we adopt the library Thrust [3] for the use of several efficient data-parallel primitives such as parallel scan, segmented scan, reduction, and sorting, while in [22] Tzeng and Owens develop their implementation by strongly exploiting the library CUDPP [5]. The reason why we choose to use the library Thrust rather than CUDPP is that: Thrust has been integrated in CUDA toolkit, and can be much easier to be used in practice.

### 6.2 Performance Impact of Preprocessing

We have observed that: our implementation executing in the Mode 1 is much faster than that in Mode 2; see Figure 4. This behavior is probably due to the facts that: (1) more than 50% input points can be discarded in this preprocessing; (2) the performance benefit from the discarding of interior points is more than the performance penalty lead by the discarding.

Besides the above mentioned improvement in computational efficiency, another benefit of adopting the preprocessing procedure is that: the memory usage on the device side is much less. This is because that: after the preprocessing only less than 50% input points remain. Therefore, in the subsequent procedure of computing the convex hull, it is only needed to allocate much less memory on the device side for the arrays such `float x[n], y[n], dist[n]` and `int keys[n], first_pts[n], flag[n]`.

### 6.3 Performance of Each sub-procedure

There are three main sub-procedures in our implementation when adopting the preprocessing, i.e., the preprocessing procedure (pre-step), the splitting of points into two subsets (1st step), and the recursive procedure of finding the expected convex hull (2nd step). To find the potential performance bottleneck, we have investigated the computational efficiency of these three sub-procedures; see the computational efficiency on K20c presented in Figure 5. We have found that in most cases: (1) the most computationally expensive step is the 2nd step; (2) the most computationally inexpensive one is the pre-step. Therefore, the potential performance bottleneck of our implementation is probably the 2nd step, and needs to be optimized in further work.



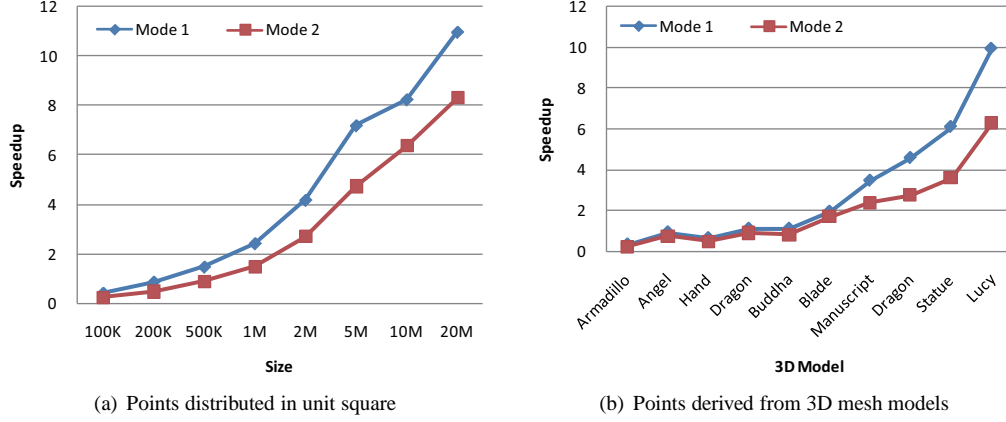


Figure 4: Comparison of speedups in two modes on K20c

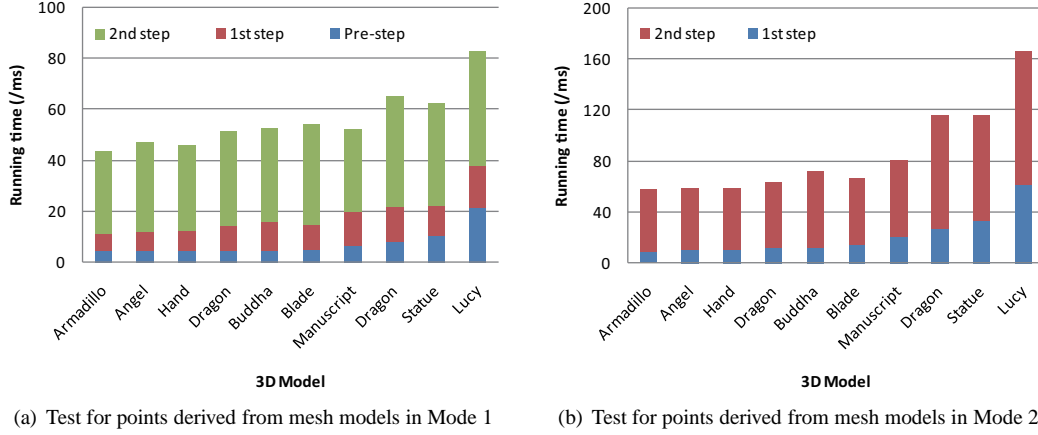


Figure 5: Computational efficiency of sub-procedures on K20c

## 7 Conclusion

We have presented a novel implementation of the two-dimensional QuickHull algorithm on the GPU. In our implementation, we have transformed the Divide-and-Conquer procedures into the operations for segments directly in the input arrays. We have strongly utilized several efficient primitives including parallel sort, scan, segmented scan, and partitioning provided by the library *Thrust*. We have also evaluated the performance of our implementation using: (1) points randomly distributed in unit square and (2) points derived from 3D mesh models with or without employing the preprocessing procedure. We have found that our implementation can achieve a speedup of up to 10.98x over the Qhull library. We have also observed that it cost about 0.2s to find the convex hull of 20M points. We hope that our work can help develop efficient implementations of other Divide-and-Conquer algorithms on the GPU.

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